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EDITORIAL

Moving Ahead with Computational Movement Analysis

“We would like to dedicate this special issue to the memory of Professor Rein Ahas (1966 - 2018), a pioneer of computational movement analysis and mobility analytics, who sadly and very unexpectedly passed away shortly before this issue went to print.”

1. Introduction

The growth of computational science has been observed as a multidisciplinary trend in the late 20^{th} century and is one which has been well documented within Geography and GIScience as well as many other disciplines. Computational movement analysis (the topic of this special issue) reflects the embeddedness of computational thinking and methods in modern movement data analysis (Laube, 2014).

Studying how things move is an inter-disciplinary problem (Demšar et al., 2015) and one that reflects the diversity of domain research interests within GIScience. For example, in this special issue, applications include both human (including pedestrians, fleet vehicles, cyclists) and animal movement (terrestrial wildlife, birds, and livestock). One of the key challenges of current movement analysis research is the breadth of applications and methods being explored to rapidly expanding and often complex datasets across a range of research areas and spanning various spatial and temporal scales.

This special issue is a legacy of previous activities (both by the editorial team and many others) to unify the diverse research encompassed by movement analysis under the banner of GIScience and consolidate movement-related research literature. Specifically, this special issue was proposed as part of a pre-conference workshop on movement analysis at the GIScience meeting, Sep. 27-30, 2016 in Montreal, Canada. A number of previous special issues within IJGIS complement the suite of papers we present here. Specifically, Andrienko et al. (2010) focusses on visualization of spatial-temporal data where movement data is emphasised, Zook et al. (2015) looks at human mobility and mobile applications, Dodge et al. (2016) explores the breadth of approaches encountered in the analysis of movement data, and Shaw et al. (2016) looks at human dynamics in the big-data era. Here in this issue we focus on the development of computational methods and computational thinking in movement analysis owing to the rapid growth of movement datasets and new computational paradigms.

2. Summaries of the articles featured in this special issue

We present 12 original papers in this special issue on computational movement analysis. Given the rapid change that has occurred in the way we collect movement data (Purves, Laube, Buchin, & Speckmann, 2014), it is not surprising that many of the papers represent new methodological contributions. Over half of the papers in this issue employ large datasets comprising of over one million records, which are also being combined with ancillary data on, for example, urban structure or other environmental covariates. All papers explore computational problems associated with pre-processing, processing, linking, analysing, visualizing, and synthesising large, diverse, and complex movement datasets and how they are influenced by underlying geographic context.

Tao et al. (2018) present a new modelling framework for movement defined by flows between spatially positioned checkpoints. Checkpoints are defined as being either transaction or presence-based checkpoints. The modelling framework is easy to comprehend and makes the contribution of defining how transaction and presence-based sensors can be combined into a single analysis.

Gao et al. (2018) demonstrate an extension to the popular spatial scan statistic (Kulldorff, 1997) for movement flows between regions. The method is appropriate for both aggregate flows (e.g., origin-destinations by region, such as state migrations) and for individual spatially-explicit flows (e.g., taxi origin-destination data). Using the multi-dimensional scan statistic, the authors demonstrate how spatial hotspots can be identified within large flow datasets.

Guo et al. (2018) present a new visualization method — Spatial Tabu Optimization for Community Structure (STOCS) — for community detection in origin-destination flows. The broad applicability of the approach is demonstrated through two examples, one employing wildlife tracking data and another studying human movement behaviour from call detail records in Shanghai. Their method can detect spatial regions reflected by the movement patterns in the data. The regions can then be used, for example, to characterize boundary features associated with movement patterns.

Kempinska et al. (2018) develop a new method for studying interactional regions, as a way to derive spatial communities from network-based movement data. GPS traces of police patrol vehicles in London, UK are used to demonstrate how the method can be applied in practice. Interactional regions are densely connected areas within the network. They represent fine-scale mappings of movement flows along edges in a spatial network and, in particular, this method is able to detect longer activity movements, for example between key nodes.

Wang et al. (2018) present a new spatial optimization algorithm to study meet-up locations in an urban context. Specifically, a network-based algorithm is employed to identify optimal, centrally located meet-up locations between two or more individuals. The method is demonstrated on simulated meet-up scenarios on actual road and POI datasets. The approach has significant potential for adoption in location-based mobile applications.

Hwang et al. (2018) demonstrate a new segmentation method for partitioning movement data into stops and moves. The focus of this paper is especially important as the method is demonstrated using high resolution (< 10 seconds interval) GPS tracking data. A fuzzy inference approach is taken, which allows it to be particularly sensitive with data that contains significant time gaps, a common problem encountered in GPS tracking studies.

Yang & Gidófalvi (2018) present a data mining approach for visualizing recurrent and sequential patterns in large tracking datasets. They propose what they call a Bidirectional Pruning based Closed Contiguous Sequential Pattern Mining (BP-CCSM) algorithm, which draws on frequent-pattern trees to derive movement pattern sequences within the tracking data. Then a visualization tool called the Spatial Pattern Explorer for Trajectories (SPET) is developed to explore recurrent and sequential patterns within the larger dataset.

Loglisci (2018) presents a new approach for studying interactive groups, called 'crews', in movement databases. The definition of crews is more relaxed than previous attempts at finding groups or flocks in large tracking datasets, as crews have relaxed spatial and shape constraints in comparison with other approaches (Benkert, Gudmundsson, Hubner, & Wolle, 2008). Specifically, the crews approach considers both the movement patterns of each individual and pairwise interactions between individuals. An efficient algorithm for processing crews in large datasets is also proposed.

Skov-Peterson et al. (2018) study navigational preferences by cyclists in the Netherlands using an edge-based route choice model, which is a local approach to wayfinding (termed locomotion). They find that there is evidence that such localized models of route choice perform better than global-path based analysis, and that local, edge-based route-choice models offer new potential for understanding human navigation and wayfinding. The implications of this research are that cyclists may be making navigational decisions locally in conjunction with global knowledge when travelling and future modelling efforts should account for this.

Paul et al. (2018) explore the question how much GPS tracking data is sufficient for delineating human activity spaces. A mobile-phone based tracking application is used to study different cohorts of student participants and to derive spatial measures of activity spaces at incrementally increasing time periods. They find that an approximately 2-week period was sufficient for generating spatially stable activity spaces. The implications of this research are clear for the design of future tracking studies, relating directly to privacy concerns of individual participants.

Downs et al. (2018) study differences in methods for mapping spatial ranges in wildlife tracking studies. Specifically, the time-geographic density estimator (TGDE) is compared with two commonly used home range estimators, a classical kernel density estimation and characteristic hull polygons. A simulation study, using an agent-based model, of Muscovy duck movement is used to test each method and provide a cross-comparison. In their analysis kernel density estimation performed worse than both TGDE and characteristic hull polygons and TGDE was found to be comparable to characteristic hull polygons for estimating home range areas, but more accurate at estimating core areas.

Liao et al. (2018) present a study of the movement behaviour of free-ranging cattle tracked by GPS collars in southern Ethiopia. Satellite and environmental data are combined with the high-resolution GPS tracking data along with in-situ videography used to ground truth different behaviours. From statistical models, they demonstrate that different behaviours are associated with different movement velocities and environmental covariates. Their findings on how cattle use foraging resources has important implications for rangeland management in the region.

3. Computational Movement Analysis: A Possible Future

As demonstrated by the rich content of this issue – and comparing with previous special issues edited by some of us (Purves et al., 2014; Dodge et al., 2016) – computational movement analysis continues to be a strongly developing research domain. At the workshop leading up to this special issue a panel session was thus devoted to discussing future research trends. In the following, we briefly touch on a selection of points that were mentioned in the panel session and that found the support of the workshop participants, without claim of completeness.

3.1. Lagrangian vs Eulerian movement analysis

One of the key distinctions used in the analysis of movement data is the choice of a Lagrangian or Eulerian world-view (Laube, 2014). Specifically, the Lagrangian view involves tracking individuals directly, while the Eulerian view involves monitoring individuals as they pass by defined spatial locations. In practice, this relates to the type of movement data that is being explored, for example flows between nodes in a network (Eulerian; e.g., cell phone tower call records, check in/out records, or data from camera traps), or individual movement traces (Lagrangian; e.g., via GPS tracking). The distinction between these two fundamentally different world-views (and data models) is nicely demonstrated in this special issue. We have seen rapid growth of studies employing a Lagrangian approach to movement analysis and the associated methods-base in this area are substantially more developed (Laube, 2015). However, in the future we are likely to see much more Eulerian-based data associated with diverse types of technology (e.g., cell phone towers, Bluetooth beacons, WLAN hot spots, gates of public transport systems, camera traps) employed to study movement. The growth of the smart cities movement offers the potential to collect and analyse massive amounts of check-in data (e.g., bike share records, social media check-ins) and other technologies are employing similar approaches in attempt to make cities easier to navigate. Another reason we have seen rapid growth of Eulerian data in academic research is the privacy concerns associated with individual tracking (see Paul, 2018), but Eulerian data poses similar but unique challenges for maintaining individual privacy. The methods for studying Eulerian data presented in this issue (Gao et al., 2018; Guo et al., 2018; Tao et al., 2018) offer new avenues for further analysis in the Eulerian domain.

3.2. Computationally Intensive Movement Analysis

The expansion computational paradigms in both the sciences and social sciences has been enabled both by the availability of powerful personal desktop computers and the rapid development of high powered computing facilities. In the analysis of movement data, we have still only really seen developments that are taking advantage of the former. In the future, we are likely to see new algorithms capable of leveraging high-performance computing (HPC) facilities (e.g., clusters, parallel computing using graphics processing units). This may fraction the research base between those that have to the requisite expertise required to take advantage of available facilities and those that do not. The emergence of HPC practices seems all but inevitable and will continue to revolutionize modern movement analysis. As movement datasets increase in volume and complexity, techniques for processing and simplifying these datasets are necessary (e.g., many of the papers in this special issue employ datasets with millions of records). The data reduction process is especially important for high-resolution tracking data, where much of the data are redundant when studying the salient broad scale behavioural patterns. Massive movement datasets contain a wealth of information, but this can in turn lead to major challenges in visualizing and contextualizing this information. Thus, the attention of the human analyst needs to be allocated efficiently in such large movement datasets in order to reduce the overabundance effect in data visualization - as a wealth of information is known to "consume the attention of its recipients" (Simon, 1971; p40). One of the take-home messages from this special issue is that efficient tools for reducing big movement datasets almost exclusively revolve around the use of geographic space. For example, several papers in this special issue employ spatial metrics (e.g., home ranges or activity spaces) to simplify the analysis of movement data. Future work aimed at synthesising massive movement datasets should follow on this lead and explore more complex spatial methodologies. However, we should not forget about the rich temporal information stored within movement data and look to develop time-centred metrics for movement data.

3.3. Inter-individual Interactions

It is now extremely easy to collect movement data, owing to the rapid technological development of tracking systems (e.g., GPS) and embedded wireless sensors (e.g., Bluetooth). In fact, most of us readily participate in the generation of different forms of movement data on a daily basis. While most considerations of the impacts of increasing data are associated with having more data about individuals within the sample (e.g., higher resolution tracking), we are also witnessing a concurrent rapid growth in the number of individuals being tracked. The ability to simultaneously track many individuals (humans or animals) is providing new opportunities to study inter-individual dynamics within movement datasets. Within this special issue, specific papers (e.g., Loglisci, 2018; Wang et al., 2018) highlight some exciting new avenues for research in the study of inter-individual interactions. This is an area primed for more significant development within computational movement analysis.

3.4. Sensor Fusion and Data Integration

Recent advances in multi-modal sensors have enabled computational science to integrate multiple sources of data (e.g. GPS tracks, accelerometers, fitness tracking sensors) to fill information gaps and decrease uncertainty in analysis of activity patterns and increase our understanding of individual behaviour at fine levels of detail. This provides a promising opportunity to advance computational movement analysis by developing fine-scale and comprehensive movement models for understanding and predicting movement. Sensor fusion and data integration is perhaps most prominent in the domain of wildlife tracking, where we are witnessing a rapid advancement in methodologies combining remotely sensed data, accelerometer, and other on-board sensors with individual tracking devices. Designing analysis frameworks capable of integrating and synthesising these complex and diverse data sources will remain a challenge in future movement analysis.

3. Conclusion

Computational movement analysis is a rapidly expanding area of research within GIScience, but also within complementary domains. It is worth noting that two of the future research areas that we identified during our workshop were also identified in an earlier special issue (‘moving towards massive data', 'multi-sensor measurement and analysis' ; Dodge et al., 2016) which shows that these areas remain ongoing challenges within computational movement analysis. Dodge et al. (2016) and Birkin et al (2017) also identified other problem areas that remain ongoing in computational movement analysis, including prediction, multi-scale modelling, and visualization of movement. Owing to continued technological developments the breadth of movement research is still growing rapidly and offering new insights in a range of topic domains and the application of movement research continues to expand to help understand new problems (Demšar et al., 2015). This special issue highlights many of the emerging areas of research within computational movement analysis and should serve as a valuable resource for future work in this area.

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